FIELD OF THE INVENTION

The present invention relates to a method and to a system intended for real-time estimation of the flow mode of a multiphase fluid stream at all points of a pipe, comprising using neural networks.

BACKGROUND OF THE INVENTION

Transporting hydrocarbons from production sites to treating plants constitutes an important link in the petroleum chain. It is a delicate link because of the complex interactions between the phases forming the transported effluents. The basic objective for operators is to reach an optimum productivity under the best safety conditions. They therefore have to control as best they can the velocity and the temperature so as to avoid unnecessary pressure drops, unwanted deposits and unsteady flows. The method that is generally used consists in modelling in the best possible way the transportation of complex multiphase streams so as to provide at all times an image of the flows in the various parts of the production chain, by taking into account the precise constitution of the effluent, the flow rates, the pressures and the flow modes.

There are currently various software tools for simulating the transport of complex multiphase streams, allowing to design suitable production equipments at an early stage.

Patents US-5,550,761, FR-2,756,044 (US-6,028,992) and FR-2,756,045 (US-5,960,187) filed by the applicant notably describe modelling methods and tools allowing to simulate the transport of complex multiphase streams on steady or transient flow and capable of taking into account instability phenomena that occur because of the

irregular geometry of the formation crossed by the pipe or of the topography thereof, referred to by specialists as « terrain slugging » or « severe slugging ».

The simulation tools are as complex as the modelled phenomena. Precision and performances can only be obtained after a relatively long modelling time, which is not really compatible with real-time management. That is the reason why these modelling tools cannot be used as they are for real-time management of the production. It therefore appears necessary to use modelling methods offering a good compromise between calculating speed and accuracy of results.

The main objective of the invention is a method allowing, alone or in parallel with the aforementioned modelling methods, real-time management of the parameters of a fluid circulation by using neural networks.

It can be reminded that neural networks define a data processing mode simulating the functioning of biological neuron systems. In such networks, an element carries out a relatively simple calculation such as a weighted sum of the signals present at its inputs applied to a non-linear function, which determines the state of its output. A large number of such elements interconnected in series and in parallel is used. Proper selection of the weighting factors allows the network to carry out complex functions. Networks known as retropropagation networks for example use multiple layers of elements defined above. Adaptation of such a network to a precise task is done by « training » the network with a certain number of examples and by adjusting the weighting factors for each element to the suitable values. Input values are presented to the network, the output value produced by the network is analysed and the weighting factors are modified to best minimize the difference between the effective value at the

output and the expected value in the selected example. After a sufficient training period, the network is suited to respond to new input values for which the output value is not known a priori and to produce a suitable output value. In its principle, a neural network works according to a non-linear regression method which is all the more effective in relation to conventional methods.

Such networks are used in many fields such as image recognition, solution of optimization problems, etc. Initially, the neural network is a method suited for automatic classification, hence its use in particular for pattern recognition. For these applications, two types of networks can be used, the MLP (Multi Layer Perceptron) or the Kohonen networks, well-known to specialists.

The prior art in the field of neural networks is illustrated by the following references :

- Dreyfus G., « Les réseaux de neurones » ; Mécanique Industrielle et Matériaux, n° 51, sept.98,

- Lippman R.P., An Introduction to Computing with Neural Nets ; IEEE ASSP Magazine, April 1987, or

- Pinkus A., Approximation Theory of the MLP Model in Neural Networks ; Acta Numerica 1999.

Networks are now also used for non-linear modelling of static data or of dynamic processes. The MLP networks are mostly used in this case. This approach currently concerns fields of application such as, for example, anomaly detection or stock-exchange prediction.

An example of use of neural networks is described for example in patent FR-A-2,786,568 filed by the applicant.

SUMMARY OF THE INVENTION

In the context of production management, the phenomena to be modelled in real time are highly non-linear and the parameters involved in the modelling procedure are numerous.

The object of the invention is a method intended for real-time estimation of the flow mode, at all points of a pipe whose structure can be defined by a certain number of structure parameters, of a multiphase fluid stream defined by several physical quantities and comprising at least a liquid phase and at least a gas phase, characterized in that modelling of the flow mode comprises :

- forming a non-linear neural network with an input layer having as many inputs as there are structure parameters and physical quantities, an output layer having as many outputs as there are quantities necessary for estimation of the flow mode and at least one intermediate layer,
- creating a learning base with predetermined tables connecting various values obtained for the output data to the corresponding values of the input data, and
- determining by iterations weighting factors of the activation function allowing to properly connect the values in the input and output data tables.

The method also preferably comprises an analysis of the output data of the neural network allowing to sort, among the values of the output data of the neural network,

only the pertinent data to be taken into account for iterative determination of the weighting coefficients of the activation function.

A neural network expresses a continuous mathematical function between input and output data. As it continuously produces results through direct calculations that permanently connect input and output data, the discontinuities linked with the solution of systems of equations are consequently avoided, hence an appreciable time saving and simplified results. The non-linear nature of the activation functions of neural networks makes them perfectly suited for modelling of non-linear systems.

The method comprises for example forming a totally connected network and using linear output neurons.

An identity function is for example selected as the activation function.

The system according to the invention allows real-time estimation of the flow mode, at all points of a pipe whose structure can be defined by a certain number of structure parameters, of a multiphase fluid stream defined by several physical quantities and comprising at least a liquid phase and at least a gas phase. It comprises :

- means for determining the characteristics of a non-linear neural network with an input layer having as many inputs as there are structure parameters and physical quantities, an output layer having as many outputs as there are quantities necessary for estimation of the flow mode and at least one intermediate layer,
- means for storing a learning base with predetermined tables connecting various values obtained for the output data to the corresponding values of the input data, and

- means for determining by iterations weighting factors of an activation function allowing to properly connect the values in the input and output data tables.

The system preferably comprises means for analysing output data of the neural network allowing to sort, among the values of the output data of the neural network, only the pertinent data to be taken into account for iterative determination of the weighting coefficients of the activation function.

The system developped by this technique can be used for example in place of a tool developped with a conventional technique (and therefore relatively slow) in order to provide results compatible with real-time stream management. The terms of this implementation are developped hereafter.

BRIEF DESCRIPTION OF THE DRAWINGS

Other features of the method according to the invention will be clear from reading the description hereafter, with reference to the accompanying drawings wherein :

- Figure 1 shows an example of a neural network formed to connect hydrodynamic input data to output data relative to flow modes, and

- Figures 2 and 3 illustrate two different topological neighbourhood cases leading to a different qualification of output data in a validation process of the neural network.

DETAILED DESCRIPTION

1) Context

We consider a circulation of multiphase fluids in a pipe with at least a liquid phase and at least a gas phase, and we try to form a neural network allowing, from a certain

number of geometrical and physical input data relative to the pipe and of physical data relative to the fluids, to give instantly, for each section of the fluid stream, an estimation of the flow mode.

2) Input and output data

The input data are for example :

- geometrical data of the network : diameter, roughness and angle of inclination of the pipe,
- input data qualifying the effluents : density of the gas, density of the liquid, viscosity of the gas, viscosity of the liquid, etc. ;
- input data characterizing the mixture : gas/liquid surface tension, volume fraction of gas, barycentric velocity of the mixture.

The data that the network will evaluate and deliver at two main outputs are :

- dV, the velocity difference between gas and liquid, and
- β, the stratified flow fraction in the pipe section where the flow type is to be determined ; $\beta \in [0 ;1]$.

Other quantities qualifying the flow type can be calculated from these two outputs.

3) Structure of the network

In order to connect the input data to the output data, a preferably MLP type neural network, well-known to the man skilled in the art, is formed since it is particularly well-suited for physical phenomena modelling. In fact, its structure allows to describe the dynamic as well as the static components of the phenomena, even by fixing, if

necessary, some of its parameters at a reified value, therefore physically representative. Thus, in the example, knowing physical equations that govern the flows allows to enrich the network and to best adapt it to the physical phenomena modelled thereby.

The neural network comprises (Fig.1) three layers : the input layer consisting of ten neurons corresponding to the ten data (mentioned above) of the complete physical model, an output layer consisting of two neurons corresponding to the two parameters dV and β sought, and an intermediate layer, referred to as hidden layer, whose number of neurons N_c is optimized. The network is totally connected. The non-linearity of this network is obtained by a sigmoid activation function governing the behaviour of the neurons in the hidden layer. The neurons of the output layer can be selected linear or non-linear. The activation function can be the identity function for example.

4) Learning : principle and implementation in the example

a) Principle

The weights of this structure are determined at the end of a learning stage ; this stage consists in supplying the network with a set of data forming the learning base of the network, and in optimizing the weights of the network by minimizing the errors noted for all the samples of the base, between the output data resulting from network calculations and the data expected at the output, given by the base. The errors can be the absolute errors between the input and output quantities or the relative errors, according to the performance desired for the network.

The generalization powers of the network are then tested from its capacity to properly calculate the two outputs for inputs that are unknown thereto.

b) Implementation

In practice, besides the difficulty in selecting the various elements making up the network, the implementation of the network requires an extensive analysis of the data that make up the learning base. In fact, even if a network is properly elaborated for a given problem, it can give in fine bad results insofar as the learning base that it is supplied with contains elements that disturb the optimization of all its weights. In the particular case of fluid flows, the problem is crucial ; in fact, flow mode calculations carried out from complete and precise models generate a highly inhomogeneous database : for example, a result indicating a stratified flow can be « drowned » in neighbouring points representing a dispersed flow : this point therefore corresponds to either a physical phenomenon that the neural network must be able to find or a « singleton » that the network has to smooth on the contrary in order to ensure the continuity of the result. The difficulty of prior data analysis thus lies in the determination of the nature of such points and, on a larger scale, of the various points of the base.

A method intended for a posteriori analysis of the network has therefore been elaborated, which identifies and distinguishes the available data representing the particular physical phenomena to be modelled from the calculation results to be ignored. This method consists in producing « compacts » around each singular point considered in the n-dimensional space of the inputs (n = 10 in the example described) in order to evaluate the degree of isolation of their behaviour ; thus, the singular points and the non-singular points are counted for each « ball » created, the proportion of singular points in the compact giving then a measure of their isolation. The terms « compact » and « ball » are taken in the topological sense of the word.

Thus, point S1 in Fig.2, which is at the centre of a ball and separated from the nearest singular point S2 by a neighbourhood of many regular points Mi, can be considered to be a singleton and thus regularized. On the other hand, the immediate neighbourhood of point S1 in Fig.3 consists of one or more singular points S2, S3, ... Sk. In such a case, one must consider that points S1 to Sk are the expression of a particular physical phenomenon that has to be taken into account by means of an adaptation of the neural network.

This selection method allows to identify the necessary points for informing the network sufficiently during the learning stage. The suitable point base thus formed can then give information thereto so as to best optimize its parameters.

5) Results

The tools and the methods described above allow to obtain :

- a database cleared of any point with an abnormal behaviour and containing only the information-rich points so as to best define the physical system to be identified,
- a network capable of interpolating the various flow types encountered so as to generate no discontinuity any longer, and also capable of taking into account the particular physical phenomena to be modelled despite their atypical behaviour, and finally
- a tool giving a real-time estimation of the main hydrodynamic information.